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A machine learning perspective on responsible gambling

In-press at *Behavioural Public Policy*

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Abstract

Gamblers are frequently reminded to “gamble responsibly.” But these qualitative reminders come with no quantitative information for gamblers to judge relative product risk in skill-based gambling forms. By comparison, consumers purchasing alcohol are informed of product strength by alcohol by volume (ABV %) or similar labels. This paper uses mixed logistic regression machine learning to uncover the potential variation in soccer betting outcomes. This paper uses data from four bet types and eight seasons of English Premier League soccer, ending in 2018. Outcomes across each bet type were compared using three betting strategies: the most-skilled prediction, a random strategy, and the least-skilled prediction. There was a large spread in betting outcomes, with for example the per-bet average loss varying by a factor of 54 (from 1.1% to 58.9%). Gamblers’ losses were positively correlated with the observable betting odds across all bets, indicating that betting odds are one salient feature which could be used to inform gamblers about product risk. Such large differences in product risk are relevant to the promotion of responsible gambling.

Introduction

Consumers purchasing gambling and alcohol products receive similar advice. “Please gamble responsibly” is seen perhaps as frequently as advice to, “please drink responsibly.” But how should this advice be followed? With alcohol, the familiar alcohol by volume percentage (ABV %) tells consumers about product strength, and this information is further broken down into the number of units of alcohol per serving on the majority of alcohol sold in the UK (Portman Group, 2017). In gambling, a similar percentage determines product strength in terms of statistical risk, but this advice is given to consumers more inconsistently. Electronic gambling machines are one UK gambling product coming with product risk information, where by law statistical risks are presented as (J. Parke, Parke, & Blaszczynski, 2016):

$$\text{“return-to-player” \%} = 100 - \text{house edge}$$

And the return-to-player percentage is described for example in practice as, “This game has an average percentage payout of 97.3%.” The return-to-player corresponds to the long-run proportion of every £100 wagered which gets returned to gamblers as prize money. The gambling operator keeps the remainder as the “house edge”. House edge will be used here in contrast to return-to-player, as a higher house edge represents a higher average risk (Woolley, Livingstone, Harrigan, & Rintoul, 2013), mirroring the risks of high ABV% alcohol. In European roulette for example the house edge on all bets is 2.7% (return-to-player of 97.3%), and this forms the basis for many roulette-based electronic gambling machine games. Qualitative research suggests that many regular gamblers fail to see UK electronic gambling machines return-to-player warning labels (Collins, Green, d'Ardenne, Wardle, & Williams, 2014), and that some gamblers do not understand the return-to-player percentage (Collins et al., 2014; Harrigan, Brown, & Barton, 2017; Rowe et al., 2017). Despite these

current failings, evidence from the behavioral risk communication literature suggests that this information could be communicated to more people through the use of graphical risk representations,(Garcia-Retamero & Cokely, 2017), while the tobacco literature suggests that making these warning labels more prominent should also boost effectiveness (Hammond, 2011) . But despite these significant failings, many UK gambling products are marketed with even less product risk information than is currently given on return-to-player warning labels.

Soccer is the UK's national sport, and soccer betting is now the most popular form of gambling with British problem gamblers (Gambleaware, 2017). The most common advice featuring on soccer bets, either at point of purchase or on marketing communications, is currently the generic, “when the fun stops, stop.” Absolutely no advice is given on relative product risk, even as these risks may vary substantially, in contrast to return-to-player or ABV % labels. When consumers see a soccer bet, either in a physical bookmaker, on a bookmaker's website, or in a marketing communication, they typically receive only one piece of risk information: the betting odds. For example, a bet on the correct score in soccer, “Arsenal to win by three goals to one, 25-to-1” means that gamblers will win £25 of profit for every £1 bet if the team Arsenal wins by three goals to one (Cortis, 2015). But each potential payout must be multiplied by its probability of happening in order to calculate a gambler's long-term returns. In European roulette, potential payout and event probability happen to be perfectly negatively correlated, so that the house edge is a constant 2.7%. Some psychologists have recently proposed that payout and probability are in fact negatively correlated in many real-world environments, resulting in roughly constant average expected returns (Pleskac & Hertwig, 2014). However, as we show next, the house edge can fluctuate wildly across different bet types in soccer betting.

Bookmakers rarely share past betting data with researchers (Chagas & Gomes, 2017). But the *average* house edge can be estimated indirectly in sports betting, based on

bookmakers' odds (Cortis, 2015), under the assumption that bookmakers offset the risks of different bets (Stark & Cortis, 2017). Each soccer match ends in one of three salient outcomes: home win, draw, away win. Bets on these outcomes are the oldest bets that can be made in soccer (Forrest, 2008), and will be called "home-draw-away" bets here. These events are high-profile, and are relatively few, so it should be easy for gamblers to shop around and find the bookmaker with the best home-draw-away odds, especially with odds comparison sites such as oddschecker.com. And the house edge on home-draw-away bets has decreased in recent years (Buhagiar, Cortis, & Newall, 2018; Constantinou & Fenton, 2013). For example, a study found home-draw-away edges of 4.5% on average over the 2014 World Cup (Newall, 2015), compared to an average house edge of 10.3% in data from the 1990s (Kuypers, 2000). But bookmakers are increasingly innovating new bet types (Newall, Thobhani, Walasek, & Meyer, 2018; Newall, 2015; Newall, 2017). Correct score bets, for example, pay off if a gambler can predict the more specific final scoreline. The same 2014 World Cup study found a far higher house edge of 21.9% on correct score bets (Newall, 2015), which is proportionally not much lower than the 26% house edge found on correct score bets from a study in the 1990s (M. J. Dixon & Pope, 2004). The house edge in soccer depends a lot on the type of bet chosen, and can be more than eight times the 2.7% European roulette house edge on a per-bet basis. This is important for gamblers, as a lower house edge allows gamblers to benefit from a lower "price" of gambling, and to thereby be able to afford a higher number of gambling experiences from some fixed budget allocated for gambling (Woolley et al., 2013).

Perhaps one of the unique attractions of sports betting is that "skilful" bettors can beat these average house edges (Kaunitz, Zhong, & Kreiner, 2017). Sports betting is a skill-based form of gambling, whereas roulette is luck-based as there is nothing that can be legally done to beat the 2.7% house edge (Thorp, 1998). The reality, however, is that many sports fans are

not especially skilled at predicting sports outcomes. Sports fans are overconfident, even when the financial stakes are high (Simmons & Massey, 2012), and are subject to wishful thinking (Babad, 1987). And soccer experts are not necessarily better than non-experts at predicting outcomes (Andersson, Edman, & Ekman, 2005; Andersson, Memmert, & Popowicz, 2009). Prediction skill means that soccer bettors can plausibly receive returns which are both better and worse than the averages summarized in the previous paragraph. This paper will therefore use machine learning to investigate the total potential impact of prediction skill across four soccer betting types. Although it could be difficult to directly make sports bettors more skilful, it might be easier to alert sports bettors to observable product features, such as the level of betting odds, which are correlated with product risk. For example with alcohol, it is reasonable to guess that the ABV% of a bottle of whiskey is higher than a bottle of wine, which is higher than the ABV% of a bottle of beer. Any salient attribute of sports bets which is correlated with the returns that gamblers receive could similarly be used to communicate product risk non-numerically.

Risks are relatively easy to estimate in electronic machine gambling, where the chance of each outcome is predetermined. This makes the house edge fixed and the winning probabilities and payoffs for gamblers easy to calculate via probability theory and Monte Carlo simulation. It is harder to calculate event probabilities in sports betting, where each match is unique, and the outcomes are governed partly by chance and partly by skill (Hill, 1974). This is one potential reason for the inconsistent labelling of product risk on UK gambling products. But consider what could happen if a gambler sees a warning label on an electronic gambling machine, but not on a soccer bet. It is possible the gambler might assume that the unlabelled soccer bet poses less risk, while actually, soccer bets can be over eight times riskier on a per-bet basis. But while it is harder to calculate product risk for sports bets,

the variable nature of sports betting risks also provides a unique opportunity to reduce the harms associated with sports betting.

Gambling-related harm increases as gamblers' total losses increase (Markham, Young, & Doran, 2014; Markham, Young, & Doran, 2016). But gamblers' losses are not fixed in sports betting, and depend on the relative skill levels across gamblers and bookmakers. At present, British bookmakers are creating soccer bets with ever increasing potential payoffs, the only piece of risk information currently communicated to gamblers (Newall et al., 2018; Newall, 2015; Newall, 2017). This matters because these high potential payoff bets have higher house edges than traditional home-draw-away bets. But changing the behavior of even a small number of gamblers, for example by making them more aware of how potential payoff combines with event probability to determine the house edge, could incentivize bookmakers to compete on "price" -- the house edge (Woolley et al., 2013). House edges have decreased for home-draw-away bets since the late 1990s (Buhagiar et al., 2018; Constantinou & Fenton, 2013; Kuypers, 2000), demonstrating that bookmakers can compete on price. Any decreases in the house edge means then even gamblers who do not change their behavior in any way can also benefit from resulting decreases in their gambling losses.

Gambling-related harm is seen as a public health problem by many researchers (Korn & Shaffer, 1999; Livingstone & Woolley, 2007; Lopez-Gonzalez, Estévez, & Griffiths, 2017; Markham & Young, 2015; Orford, 2010). Any intervention to reduce gambling's public health costs must consider the trade-off between individual freedom and protecting vulnerable consumers. At one end of the trade-off spectrum is the freedom-preserving choice to, "do nothing," while stronger interventions such as, "change the default," and, "use tax incentives," lie increasingly toward the other end (Nuffield Council on Bioethics, 2007). Providing information on product risk, for example via warning labels, is the first and most

freedom-preserving public health intervention on this spectrum. We have used the examples of alcohol and electronic gambling machine warning labels to highlight an omission of product risk information for sports bets. However, any new warning label should be trialled experimentally and in field trials before being rolled out at a population level, to ensure consumer understanding and to mitigate the risk of any behavioral backfiring (Stibe & Cugelman, 2016). Any gambling warning label should also ideally leverage insights from the behavioral risk communication literature (Garcia-Retamero & Cokely, 2017), which current UK electronic gambling machine labels do not (Collins et al., 2014; Rowe et al., 2017). And, if warning labels are not effective at protecting consumers, then stronger public health interventions should also be considered (Nuffield Council on Bioethics, 2007). These are all important goals for future research. This paper tackles a more fundamental issue in soccer betting: risks must be understood before they can be communicated.

This paper will use machine learning to investigate how product risk varies across the largest dataset of past betting odds and results available to us. The aim is to uncover information relevant to the concept of “responsible gambling”:

“If gambling is to be conceptualized as a leisure activity to be engaged in as an individual choice, ..., then it is fundamental that the individual is presented with all relevant information, in a timely fashion, in order to make an informed choice.” (A. Parke, Harris, Parke, Rigbye, & Blaszczyński, 2015), p. 31.

This will be operationalized through three research questions:

RQ1. What is the variation in prediction skill across four key soccer bet types?

Prediction skill matters to the extent that some gamblers can achieve better returns than others. Our machine learning model will make bets across different soccer matches and

bet types. We have data for home-draw-away, correct score, and two other bet types (explained in the “Data” section below). The model will do this with three strategies, to mimic the variability across human sports bettors. Model performance will then be compared across bet types and strategies, using the strategies’ arithmetic average returns for comparison. If a gambler approaches a given bet type with a given strategy, this percentage gives the amount of staked money lost on average *per bet*.

Some human sports bettors try to get the highest return possible, by inspecting recent performance and developing knowledge about the sport. This strategy will be mimicked by a strategy we call “most-skilled.” The existence of skill can be demonstrated via showing an improvement in performance over a strategy which requires no skill (or knowledge). Therefore, to check the validity of our machine learning model, a second strategy called “Random” will be generated. For RQ1, Random places a bet on *every* available outcome within a bet type. For RQ1 this generates more precise estimates of what a truly random betting strategy will return than just selecting one bet at random. It should be the case that the most-skilled strategy yields higher returns than Random. However, if it’s possible to beat a random strategy, then it’s also possible to do worse than a random strategy. But there should be limits to how bad a strategy can do, as even the most unlikely events do eventually happen in sports betting (such as Leicester FC winning the 2015/2016 English Premier League). Our machine learning model will mimic the worst returns a human might get, via the “least-skilled” strategy. For RQ1 we hypothesize that the returns will be distributed within each bet type as: most-skilled > Random > least-skilled. Prediction skill likely matters more for some bet types than others, and this will also be investigated in RQ1.

RQ2. A gambler starts with £100 and bets 10% of her “bankroll” on each game. How long will her stake take on average to fall to £50 (the “half-life”)?

RQ1 provides the best estimates of the returns from placing a single bet, under those three strategies. But many gamblers place sequences of bets from a given starting amount of dedicated gambling money, called a “bankroll.” Average arithmetic returns provide an incomplete picture for such sequences of gambles (Chen & Ankenman, 2006). RQ2 attempts to mirror the returns of the three strategies (most-skilled, Random, and least-skilled), as measured by the number of bets before half an initial amount of money is lost, on average. This should provide a more accurate measure of what repeat gamblers could experience. This research question is motivated by the statistical concept of the “Gambler’s Ruin,” which shows how a gambler with negative expected returns will eventually lose all their money (Harik, Cantú-Paz, Goldberg, & Miller, 1999; Mohan, 1955). The 10% proportion was chosen heuristically by us, in the absence of us having any human betting data to compare against (Chagas & Gomes, 2017). Larger percentage bet sizes can compress the differences between betting strategies, for example, with a bet of 50% one losing bet hits the “half-life” definition. Smaller bet sizes can do the opposite, as gamblers’ bankrolls asymptote toward lasting forever.

As with RQ1, it should be the case that, within each bet type, the strategies have half-lives of: most-skilled > Random > least-skilled. For RQ2, Random involves randomly picking one bet per bet type. This is because betting on every outcome, as in RQ1, creates a portfolio of offsetting bets which loses a small amount of money with certainty, due to the house edge, leading to an artificial boost in the bankroll half-life (and no gambler would enjoy losing a small amount of money with certainty). RQ2 therefore investigate how gamblers’ bankrolls evolve across different betting strategies and bet types.

RQ3. Which specific outcomes within each bet type do the most- and least-skilled prediction strategies tend to choose?

Machine learning should ideally provide insights to help human decision makers. Humans often overestimate the likelihood of low-probability events (Kahneman & Tversky, 1979). This tendency has been reflected in sports betting via the “favorite-longshot” bias, where longshots with low winning chances yield higher an average losses for gamblers than bets on favorites (Vaughan Williams, 1999). Favorite-longshot bias has been observed in large dataset investigations of home-draw-away soccer odds (Buhagiar et al., 2018; Constantinou & Fenton, 2013). Ideally, the least-skilled strategy will look like a biased human sports bettor, while the most-skilled strategy will bet differently. Looking at recurring features of the specific bets chosen by the most- and least-skilled strategies could also help inform strategies intended to educate gamblers about observable bet attributes which are correlated with product risk.

Model

Machine learning models come in varying degrees of complexity. Innovations in machine learning research often focus on new techniques for processing large amounts of data. Our intention with this paper was not to innovate new machine learning techniques, but to apply established prediction models from the operations research literature to the topic of responsible gambling. Better machine learning models will always be possible. However, any improvement in prediction should not necessarily bias our estimates of different betting strategies’ *relative* risks. Our key innovations are to consider the total impact of skill, via comparing the most- and least-skilled strategies, and to use the most extensive freely-available dataset of soccer betting odds (four bet types over eight seasons). We encourage other researchers to attempt to replicate these results with different datasets and models.

Data

We wanted to train the model on as many bet types as possible, given the ever-increasing number of ways to bet on soccer. However, long-running freely-available datasets were required, limiting the number of bet types that could be studied. Historical odds were available for the following four betting types: correct score, home-draw-away, over/under, and Asian handicap. Data for eight seasons of English Premier League soccer (the highest English club competition) betting odds and results from 2010/2011-2017/2018 were taken from oddsportal.com.

Summary information is provided in Table 1. Of the four bet types, correct score bets stand out as an outlier in Table 1 with 25 potential outcomes. Although there is in theory no limit on the number of goals scored by both teams in a soccer match, reliable data were available only on the 24 most common scorelines. All other potential scorelines were included as a 25th catch-all outcome in the model. Home-draw-away bets have three potential outcomes (home win, draw, away win). The over/under is a bet on the number of goals scored: to be either between zero and two goals, or three or more goals (two potential outcomes). The Asian handicap performs a skill adjustment on the two teams, effectively removing the potential of a draw (e.g., Arsenal to win by 1.5 goals or more, therefore two potential outcomes).¹ “Complex” bet types with many potential outcomes, such as correct score bets, have previously been associated with high house edges (Ayton, 1997), and an overestimation by soccer fans of average event probability (Newall, 2017).

Table 1. Example of betting odds data

Betting market	Example	Number of potential outcomes
Correct score	“Arsenal to win 1-0”	25
Home-draw-away	“Arsenal to win”	3
Over/under 2.5 goals	“Over 2.5 goals to be scored in the match”	2
Asian handicap	“Arsenal to win by 1.5 goals or more”	2

Note: Although there is potentially an infinite number of potential correct scores, reliable betting odds were only available for the 24 most-likely scorelines. Therefore, we include these 24 scorelines (either team scoring up to 4 goals, excluding 4-4) while adding a 25th catch-all outcome for any other scoreline.

The model was also given in-game statistics of recent team performance (explained at greater length in the Inputs section, below). This data was downloaded from football-data.co.uk.

Model specifications

Machine learning models approach new data sets like a cautious gambler, learning patterns between current data and future outcomes, before making any predictions (the learning phase). The first three seasons were solely used to learn from the data.² Prediction quality on these learned associations was then assessed only in a new, unseen part of the data (the prediction phase). From the fourth season on, the model strategies placed (simulated) bets and received hypothetical returns. Because old data becomes gradually less informative, each season of prediction was based only on the previous three seasons of learning.

An emphasis on predicting new data is a hallmark of the machine learning approach to statistical testing. Less emphasis is placed on interpreting p -values, as in traditional null hypothesis statistical testing. The main check on model validity is that the most- and least-skilled model strategies should perform better and worse than Random in the prediction phase. Some researchers have argued that the social sciences could benefit from placing greater emphasis on predicting new data, and less on explaining past data, as is currently done via null hypothesis statistical testing (Yarkoni & Westfall, 2017).

Prediction phase performance was available for five seasons in total: 2013/2014 – 2017/2018. Prior to running any analysis, a decision was made to discard the first five games of each season due to potentially-large between-season variations in team performance. This leaves a total sample size of 1,650 matches to compare model performance on (330 matches per-season). Each prediction is based on 990 learning phase observations (3 seasons). The required number of learning phase observations to obtain 95% statistical power is 380 for the low-complexity bet types (home-draw-away, over/under 2.5 goals, Asian handicap), and 950 for the high-complexity correct score bet type (Hsieh, Bloch, & Larsen, 1998).

Appropriate machine learning model choice depends on the underlying data's statistical properties. Some soccer forecasting models were developed for individual matches, which is typically accounted for by multinomial logistic regression models, given the three main outcomes of a soccer match (e.g., (Khazaal et al., 2012; Koning, 2000; Willoughby, 2002)). But the present model also forecasts bet outcomes, which depend on the specific teams' characteristics, where a conditional logistic regression is more appropriate (Smith, Paton, & Vaughan Williams, 2009). Each of these features needs to be accounted for separately. Therefore, we used a combination of multinomial and conditional (mixed) logistic regression to capture the full scope of the data (Lessmann, Sung, Johnson, & Ma, 2012; McFadden, 1974; McFadden & Train, 2000).

Inputs

The machine learning model, like an expert gambler, learns associations between publicly-available information (predictors) and soccer outcomes. Given the applied nature of our research questions, our aim was not to test the predictive power of previously unexplored inputs, but to only use inputs established in the previous literature to have positive predictive performance. While better models could always be designed, our relatively simple approach should not necessarily bias our estimates of different betting strategies' relative risks. It might

seem that adding more inputs should boost predictive power. However, adding more inputs can increase the risk of “overfitting,” where chance random associations are discovered and erroneously predicted to recur in the prediction phase, hence leading to poor prediction phase performance (Yarkoni & Westfall, 2017).

Our first model input was an average of relevant match betting odds, using around an average of 30 bookmakers per data point. Betting odds have shown to successfully predict outcomes in the soccer forecasting literature (Goddard & Asimakopoulos, 2004; Štrumbelj & Šikonja, 2010; Štrumbelj, 2014). Betting odds tend to fare even better than other prediction methods, such as Elo rating systems, originally designed for chess ratings (Hvattum & Arntzen, 2010; Leitner, Zeileis, & Hornik, 2010). As is the standard in the literature, these odds were averaged, to reduce random forecast error, and were normalized to remove the effect of the house edge³ (Hvattum & Arntzen, 2010; Leitner et al., 2010).

Gamblers will often factor in recent performance. Therefore, the model was provided with in-game statistics summarizing each team’s performance over the previous five matches. Based on successful in-game predictors from the previous literature, we chose the cumulative number of points earned -- three for a win, one for a draw, and zero for a loss (Goddard & Asimakopoulos, 2004; Goddard, 2005), and the number of goals scored and conceded (Angelini & De Angelis, 2017; Baio & Blangiardo, 2010; M. Dixon & Robinson, 1998; Oberstone, 2009). Predictors which have been used in the previous literature, but were not included here include the number of: corners won (Andersson et al., 2009), shots on target (Oberstone, 2009), recent injuries (Constantinou & Fenton, 2017), and disciplinary bookings (Titman, Costain, Ridall, & Gregory, 2015).

We combined the estimate of the likelihood of each event happening from the machine learning model, with the potential payoff size, to create an estimate of the expected

return from each bet with different strategies. The most-skilled strategy chose the bet with the highest long-run expected return within each bet type for each match, while the least-skilled strategy chose the bet with the lowest long-run expected return.

Results

In response to RQ1, the arithmetic average percentage returns varied over both the four bet types and the three betting strategies used, as summarized in Figure 1. Figure 1 presents the results of different hypothetical bettors, so it is more accurate to present the returns as experienced by each betting strategy, rather than as the bookmaker's overall house edge. The negative returns experienced by each strategy in figure 1 can be interpreted as showing that predictions were never able to overcome the bookmaker's house edge. A return of -3.3% is equivalent to a house edge of 3.3%, or equivalently a return-to-player of 96.7%. In each bet type it can be seen that the most-skilled prediction performed best, the least-skill strategy performed worst, and Random was in the middle. Therefore, in each bet type, (positive) betting skill improved performance, while (negative) betting skill worsened performance. Prediction skill mattered most in with correct score bets. With correct score bets, the least-skilled strategy returned -58.9% on average, Random -34.3%, and the most-skilled strategy -3.3% (returns as experienced by the model). No other betting strategy experienced returns worse than -10% per-bet (even the least-skilled strategies). And in the other three bet types, the per-bet difference in returns across the three betting strategies was 7% or under. Prediction skill always mattered, but especially with correct score bets (where there were many potential outcomes).

Next we investigated the variation in relative betting performance. Comparing the relative losses can indicate the potential magnitude of savings a gambler could make by shifting toward lower "price" bets. Table 2 shows each loss as a multiple of the lowest-loss

performance, which was most-skilled Asian handicap, -1.1%. The variation in relative performance was large. The least-skilled correct score strategy lost 54.0 times more per-bet than the lowest-loss performance. High relative losses were not unique to correct score bets, with for example the least-skilled home-draw-away strategy losing 8.0 times more per-bet than the lowest-loss performance.

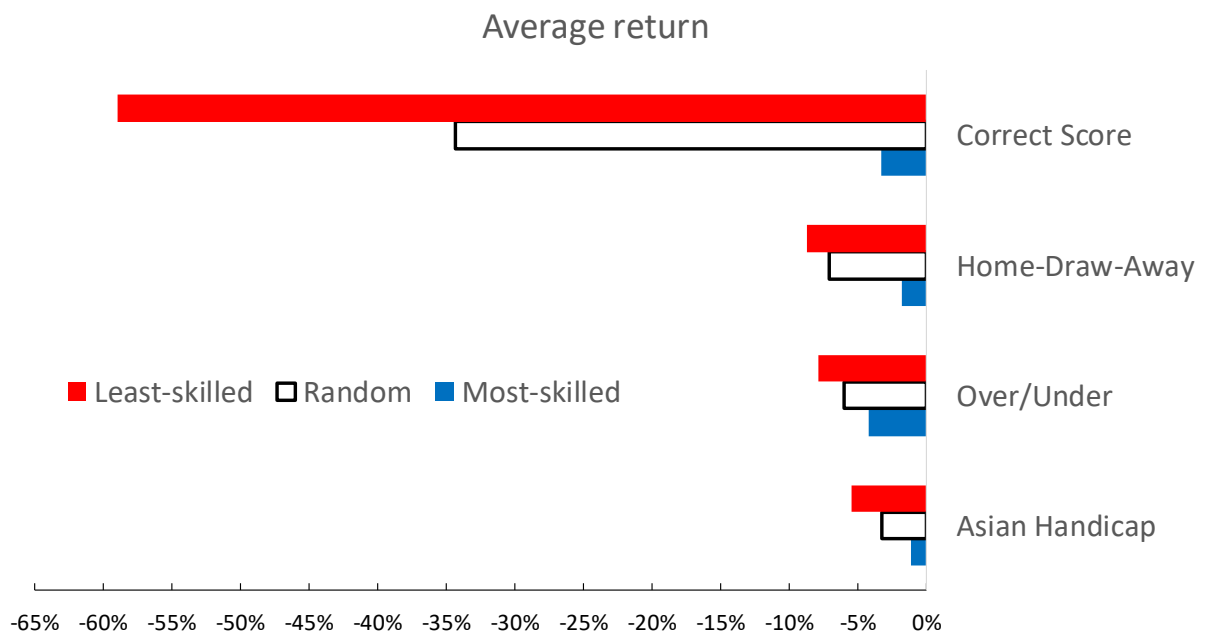


Figure 1: Prediction skill variability over each bet type and strategy.

Table 2. Relative per-bet losses (in percentages), standardized so the lowest loss strategy (Asian handicap, most-skilled) = 1.

Strategy	Correct Score	Home-Draw-Away	Over/Under	Asian Handicap
Least-skilled	54.0	8.0	7.2	5.0
Random	31.5	6.5	5.5	2.9
Most-skilled	3.0	1.6	3.8	1.0 (-1.09%)

The half-life measured the number of bets before an average of 50% of starting wealth was lost (betting 10% of remaining wealth per-match). Half-life variation is summarized in Figure 2, in response to RQ2. Similar to Figure 1, the most-skilled strategy had the highest half-life across each of the four bet types, and the least-skilled strategy had the smallest half-life. Correct score bets had half-lives of 10.8 to 7.0 bets, making it an outlier compared to the other three bet types. The other three bet types had *least*-skilled half-lives of 22.2 (home-draw-away), 52.2 (over/under), and 64.4 bets (Asian handicap), all performing better than the most-skilled correct score strategy. A comparison of relative half-lives in Table 3 highlights the large differences. The highest half-life strategy (Asian handicap, most-skilled, 129.6 bets), lasted 18.5 times the lowest half-life strategy (correct score, least-skilled, 7.0 bets). There was again a large spread in betting outcomes, as measured by the half-life. All correct score betting strategies had low half-lives because this is the most volatile bet type.

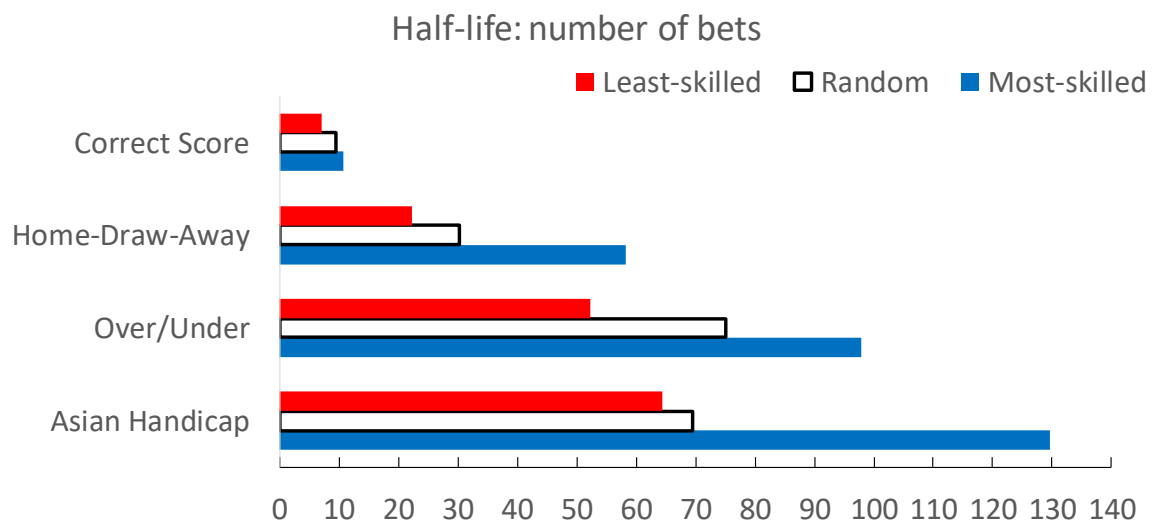


Figure 2. Half-life variability over each betting market and strategy.

Table 3. Relative half-lives (in number of bets), standardized so the lowest half-life strategy (Correct score, least-skilled) = 1.

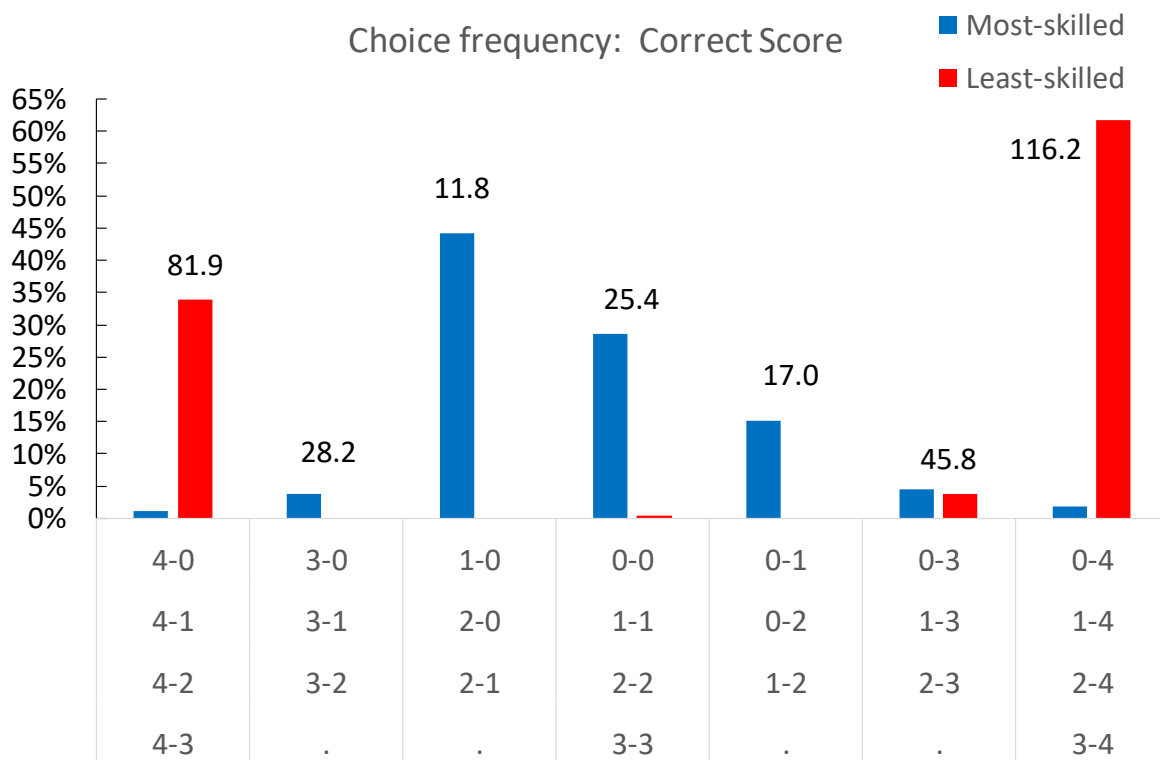
Strategy	Correct Score	Home-Draw-Away	Over/Under	Asian Handicap
Least-skilled	1.0 (7.0 bets)	3.2	7.5	9.2
Random	1.3	4.3	10.7	9.9
Most-skilled	1.5	8.3	14.0	18.5

Next we investigated the outcomes chosen by the most- and least-skilled prediction strategies across each bet type. Figure 3 provides an answer to RQ3. There are clear differences, as the most-skilled strategy preferred low-scoring home wins with correct score bets (panel a), and home wins with home-draw-away bets (panel b). Figure 3 also provides the average decimal odds across each outcome shown on the x-axis. The decimal odds represent the total payoff from a successful bet of \$1 (Cortis, 2015). The higher the decimal odds, the more extreme a longshot the bet is. In soccer, the team playing at home is usually the favorite to win (due to home advantage). By convention, the home team's score is written first, so a scoreline of 2-0 translates to the home team scoring twice and not conceding.

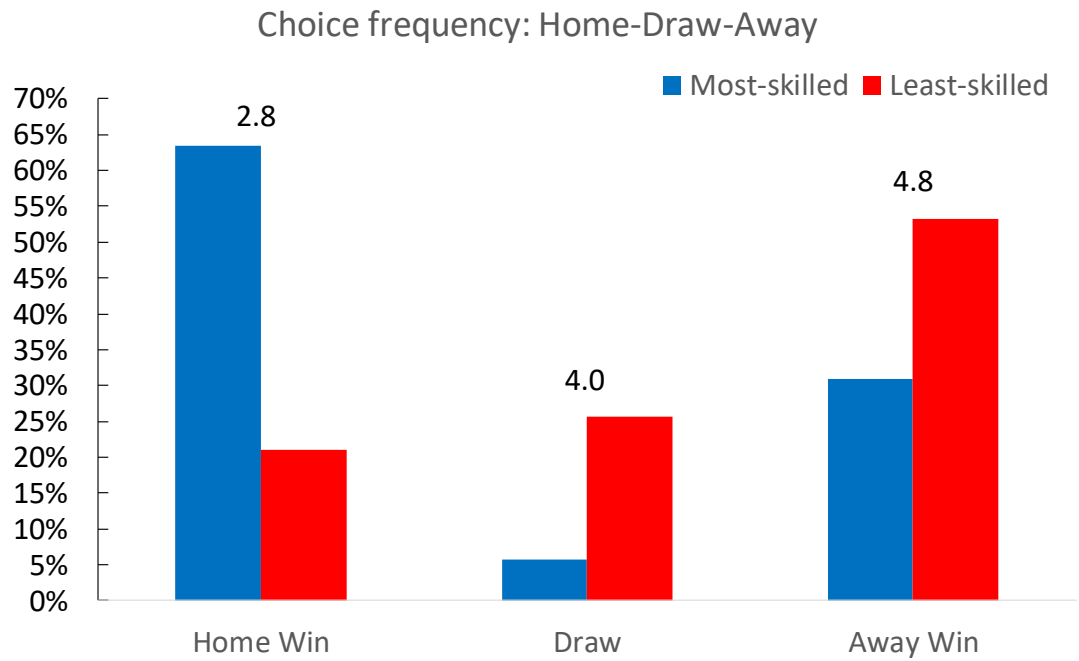
Across each bet type, the most-skilled strategy usually chose likely outcomes with low decimal odds. For example, the home team winning 1-0, 2-0, or 2-1 with correct score bets was chosen 44.1% of the time (average decimal odds = 11.8), and the home team winning in home-draw-away was chosen 63.4% (average decimal odds = 2.8). The most-skilled strategy also favoured the home team winning in the Asian handicap, and Over 2.5 goals in the over/under. By contrast, the least-skilled strategy chose the most extreme outcomes. This is demonstrated best with correct score bets, where the least-skilled strategy places more than 95% of its bets across either the away team winning and scoring four goals (61.7%, average decimal odds = 116.2), or the home team winning and scoring four goals

(33.9%, average decimal odds = 81.9). (Each scoreline is estimated separately by the models, we have grouped similar scorelines together for simplicity.) The most-skilled strategy tended to bet on favorites, while the least-skilled strategy tended to bet on lower-probability longshots, reflecting the established human bias of overweighting small probabilities (Kahneman & Tversky, 1979)

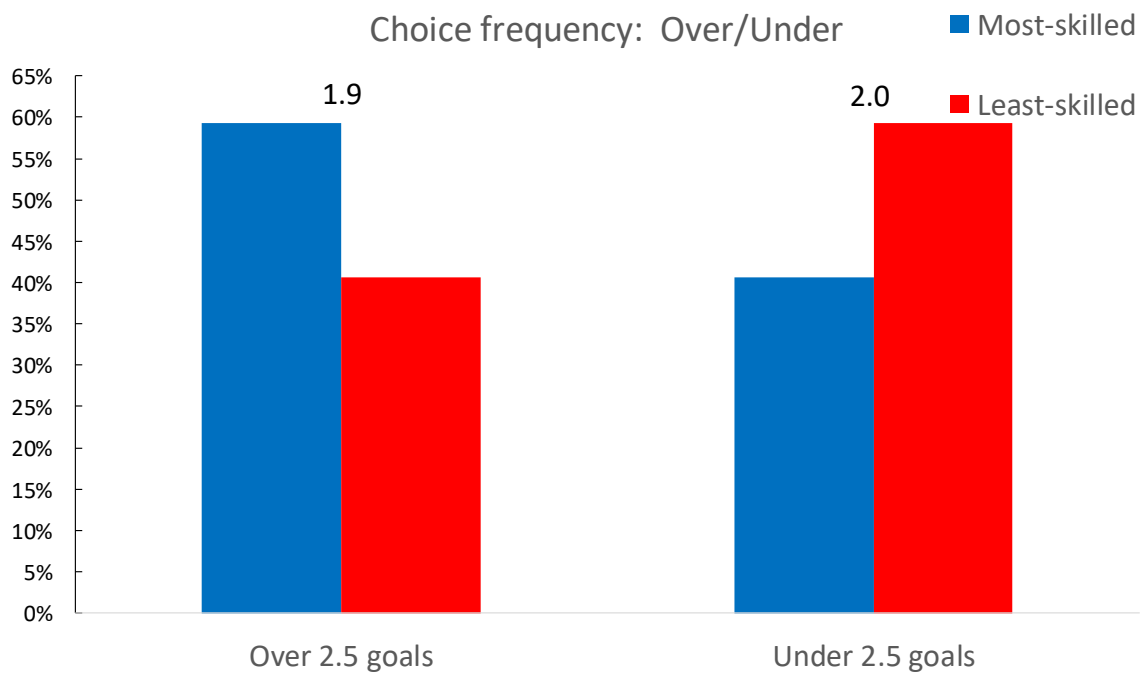
a)



b)



c)



d)

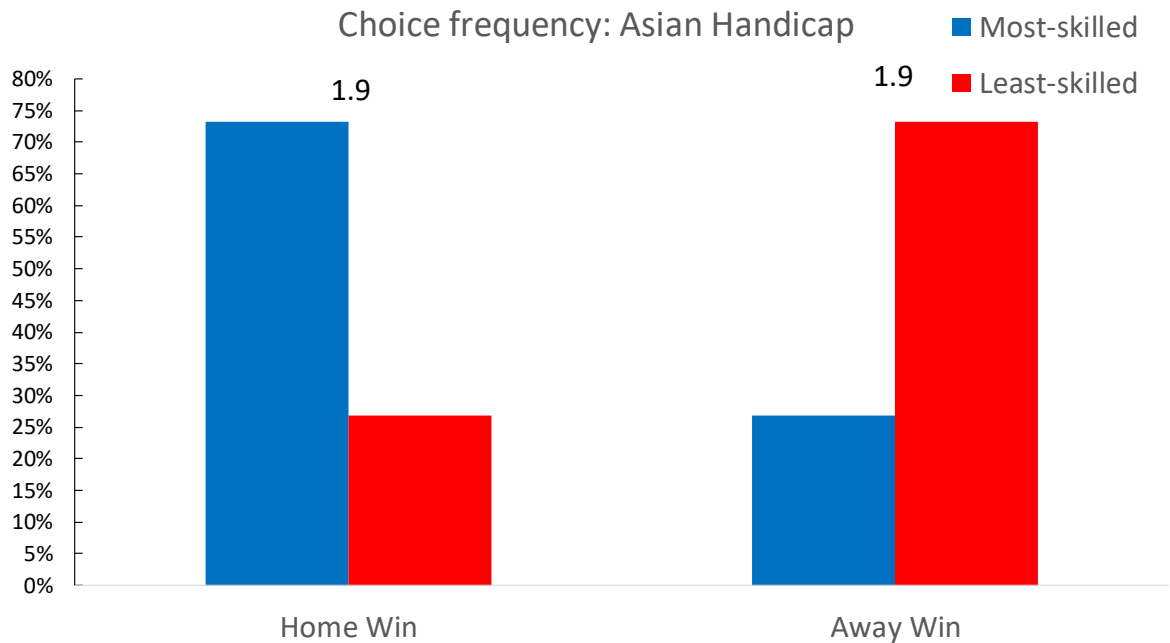


Figure 3. Most- and least-skilled specific choice frequencies across each betting market. The decimal odds are shown above each x-axis category, showing the total average payoff from a successful bet of \$1. Similar scorelines were grouped together in panel a), although the model estimates frequencies for each scoreline separately. By convention, scorelines are written as home team score - away team score.

Discussion

The introduction called soccer betting a “skill-based gambling form.” In support of this claim, it was found that prediction skill mattered in each of the four soccer bet types. Most strikingly, it was found that the gamblers’ losses varied by a factor of 54 (from 1.1% to 58.9%). To return to the alcohol ABV% comparison from the Introduction, this is like the difference between a reduced-alcohol lager and a strong whiskey. Meanwhile, the “half-life” number of bets before a starting bankroll fell in half varied by a factor of 18.5 (from 7.0 to 129.6 bets). The large number of outcomes makes every correct score bet a longshot with

correct score bets, compared to the three other bet types. Usually starving, but occasionally feasting, is a poor way to maintain wealth on average over time. This suggests that responsible gamblers should limit their exposure to volatile bet types such as correct score bets. The least-skilled strategy tended to bet on lower-probability longshots, reflecting the established human bias of overweighting small probabilities (Kahneman & Tversky, 1979). But how else might these results be relevant to the topic of responsible gambling in humans?

The wide variation in gamblers' losses here contrasts with European roulette, where each possible bet has a constant house edge of 2.7%. This variability in soccer betting only increases the amount of information which should be given to gamblers, in keeping with responsible gambling principles (A. Parke et al., 2015). But at present, UK soccer bets are marketed with only the betting odds, and generic advice such as, "when the fun stops, stop." By contrast, the more informative house edge is currently communicated to electronic machine gamblers as the "return-to-player" percentage (J. Parke et al., 2016). And, from April 2019, a £2 wagering limit will be placed on UK electronic gambling machines (Casey, 2018). By comparison, soccer betting, which is the most popular form of gambling with British problem gamblers (Gambleaware, 2017), has seen neither element of consumer protection.

Providing more information to soccer bettors could be seen as an informational "nudge" (Thaler & Sunstein, 2008), as an example of "boosting" (Hertwig, 2017), or of consumer education (Peters, 2017). Figure 4 provides an example of how more information could be given for home-draw-away and correct score bets, the two bet types from this paper which have been seen in observational studies of UK gambling advertising (Newall et al., 2018; Newall, 2015; Newall, 2017). Figure 4 provides a prototype example of how the gamblers' losses for the Random and least-skilled strategies could be communicated to soccer bettors. In keeping with the spirit of alcohol ABV% labels, it might be wise to not present too

much information to consumers, such as the most-skilled strategy returns, which could plausibly cause confusion given that sports fans are prone to wishful thinking (Babad, 1987).

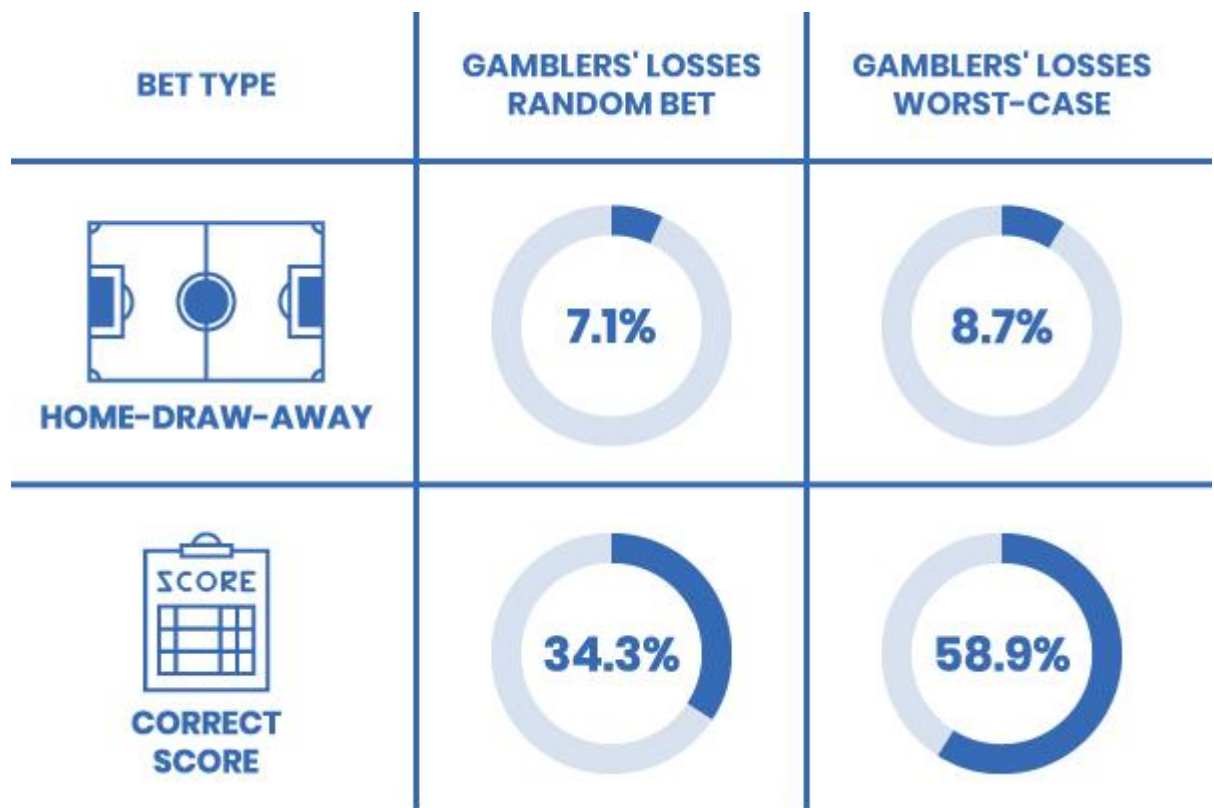


Figure 4. Example of warning labels for home-draw-away and correct score markets.

The “worst-case” column corresponds to the returns of the least-skilled prediction strategy.

But Figure 4 presents just estimates based on our historical simulation of eight seasons of data, the largest dataset available to us. Because the risks of sports betting are not fixed, it is important to present gamblers with the most up to date information. We did not have access to actual past betting data for this paper, and so were forced to use the Random strategy as a proxy for gamblers’ average losses. Replacing this figure with gamblers’ past average losses for a given bet type over some recent time horizon is one way that Figure 4 could be improved upon. The timely communication of gamblers’ past losses could also help bookmakers who plan to increase their customer base by competing on price. By comparison,

some British bookmakers appear to be currently competing to create new bets with high betting odds, which consumers observe, but high hidden house edges (Newall, 2019).

There are many aspects of any new warning label which should first be empirically tested. Any new warning label should ideally be trialled in both the laboratory and in the field before being introduced into the population, to mitigate the risk of any behavioral backfiring (Stibe & Cugelman, 2016). For example, qualitative research suggests that some young drinkers use ABV% information to find cost-effective ways of maximizing their alcohol consumption (Jones & Gregory, 2009; Maynard et al., 2017). While we think that few gamblers will want to purposively maximize their gambling losses, there are other issues from other public health domains of potential relevance gambling risk communication. Any warning label should ideally be as attention grabbing as other product features. One eye-tracking study of alcohol warning labels showed that participants spent only 7% of their time looking at current UK alcohol warning labels (Kersbergen & Field, 2017). The tobacco literature demonstrates that larger warning labels are the most effective (Hammond, 2011), which is relevant to any new warning label and to present return-to-player warning labels. Previous gambling research showed that many regular electronic machine gamblers had not even seen return-to-player warning labels before (Collins et al., 2014), and that many gamblers find return-to-player warning labels confusing (Collins et al., 2014; Harrigan et al., 2017; Rowe et al., 2017). The behavioral risk communication literature suggests for example that visual aids could boost gamblers' risk understanding (Garcia-Retamero & Cokely, 2017).

Another approach is to educate gamblers not about statistical risks, but about observable features which are correlated with these risks. For example with alcohol, there are many salient product features such as alcohol type and bottle size which are correlated with ABV%. This paper found that gamblers' losses increased as the potential payoff implied by the betting odds increased, and this occurred both within and between bet types. Bets on

longshots have higher average losses than bets on favorites. This is unlike European roulette, where the potential payoff and event probability are perfectly negatively correlated to create a constant average loss of 2.7%. A public health awareness campaign could therefore seek to warn gamblers about the above-average risks of longshot soccer bets. There is some evidence that sports bettors do learn to improve their returns over time, partly by avoiding longshots (Feess, Müller, & Schumacher, 2014). This natural learning process could be enhanced with more explicit advice.

It could be the case that warning labels and education campaigns are an insufficient intervention to debias consumers about the complex statistical information underlying modern soccer bets (Weiss-Cohen, Konstantinidis, Speekenbrink, & Harvey, 2018), and given the messages in gambling marketing prompting more frequent and riskier gambling (Hing, Russell, Li, & Vitartas, 2018; Hing, Russell, Thomas, & Jenkinson, 2019). This may particularly be the case in soccer betting, given evidence that sports fans are prone to wishful thinking (Babad, 1987), and are overconfident even when the financial stakes are high (Simmons & Massey, 2012). If this is the case, then less freedom-preserving public health interventions should also be considered (Nuffield Council on Bioethics, 2007). For example, a stronger intervention is to “restrict choice,” which is already being used for UK electronic gambling machines, where the maximum bet size will be reduced from £100 to £2 from April 2019 (Casey, 2018). Tax incentives are also being used in UK alcohol policy, with stronger forms of alcohol being subject to different rates of tax duty than lower strength alcohol. Any public health intervention should be informed by the fundamental data on product risk which this paper attempts to uncover for soccer betting.

Gambling-related harm increases as gamblers’ total losses increase (Markham et al., 2014; Markham et al., 2016). However, the gamblers’ average losses must be combined with betting volume to determine gamblers’ total losses. But the betting volume of human sports

bettors is data that we did not have access to for this paper. Data on human betting volume could plausibly highlight a different set of high-loss soccer bets that are important for the promotion of responsible gambling. We hope that gambling operators will share more data on gamblers' actual behavior (Cassidy, Loussouarn, & Pisac, 2013), in order to determine the extent to which these machine learning strategies reflect actual differences in human betting skill, and to enable further research on responsible gambling in humans.

It might also be questioned what machine learning can do to help inform soccer bettors. Although better predictive models than used in the current paper could always be designed, this should not disqualify our inferences on different betting strategies' *relative* risks. Machine learning has progressed recently in relatively constrained skill-based decision making domains. Chess champion Garry Kasparov lost to Deep Blue in 1997. Go champion Lee Sedol lost to AlphaGo in 2016. And various top poker professionals have lost special matches to machines (Brown & Sandholm, 2017; Moravčík et al., 2017), a skill-based gambling form (Potter van Loon, van den Assem, & van Dolder, 2015). Although machine play is still imperfect for all but the simplest games, machines have attained a high enough level that experts in chess (Kasparov, 2017), go (Metz, 2016), and poker (Newall, 2013) now routinely train with machines. This suggests that machine intelligence should be good enough to inform non-expert soccer bettors as well. Using machine intelligence to inform responsible gambling strategies in humans could well become more internationally relevant over time, as the US moves toward widespread legalized sports betting (Purdum, 2018).

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Footnotes

¹ There are a small number of instances where the Asian handicap was set as a discrete number of goals, e.g. Arsenal to win by 1 goal or more. Then, if Arsenal do in fact win by exactly 1 goal, a third outcome is created where the bet neither wins nor loses, a “push.” In this instance the original stake is returned to the gambler.

² Machine learning does not have strong methodological norms over what proportion of the data to use for learning and prediction. Even for similar research questions, splits as variable as 90-10 (Harvey & Liu, 2015) and 50-50 (Bajgrowicz & Scaillet, 2012) have been observed. Given the limits on our time-series (eight seasons), we chose a conservative ratio of three learning phase seasons for every prediction phase season, to reduce potential problems from more extreme ratios. Other learning/prediction phase splits were not tested.

³ The odds used to calculate bet payoffs were only averaged, effectively mirroring the returns a bettor who chooses bookmakers randomly would face.